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Utilizing Artificial Intelligence to Solve Construction Site Layout Planning Problems

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ABSTRACT

The facilities have conflicting purposes in the available space on the construction site, increasing the transportation flow of facilities, which is the cause of the increase in project construction costs. The research is applied to solve the construction site planning (CSLP) problem that depends on the quadratic assignment model (QAP). The QAP is intended to determine the best way to allocate facilities to locations so that each facility is mapped to only one location. In contrast, every location is mapped to an exact facility to minimize product flow and distance costs. Previously, there were many ways to solve the problem by meta-heuristic method such as (GA), (ACO). This paper proposes a new hybrid algorithm (M-ALOB), to solve the problem (QAP), the goal of the problem is to solve the ground layout problem built by the quadratic assignment problem (QAP). Compare the new hybrid algorithm with previously studied algorithms (GA) and the original algorithm (ALO), giving assessment of advantages and disadvantages when applied to solving discrete problems. (M-ALOB) for stable running results, tested for stability after 30 optimal runs. The optimal outcome in Case Study 1 (M -ALOB) min=688.4 is lower than (GA) is 19.7%. And Case Study 2 (M-ALOB) min = 171,970.19 lower (GA) is 2%. The results showed that (M-ALOB) found the optimal value smaller than the algorithms (GA), (ALO). Solve the problem of arranging facilities on the ground (CLSP) to minimize the workflow, save operating costs of construction projects.

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1. Introduction

Construction site layout problems (CSLPs) refer to optimizing the layout of facilities on the construction site, serving during the construction process and is an indispensable issue in construction management [1]. This issue has been studied and explored by many experts in many fields, such as industrial management and construction architecture. Favorable site conditions will support the work to be carried out smoothly and quickly including the arrangement of temporary traffic system around the construction area, office of the command board, camp for workers, construction area, utility areas, construction equipment.

The problem of facilities on the ground in other fields and environments, such as in the production environment, the appropriate design of the total facilities layout ground, and the service system will respond flexibly to the frequent spatial changes in the production process [2]. In a warehouse or storage environment, poor facilities layout will lead to inventory and overload of material handling during work and long-waiting goods. Effective layout planning will save about 10%–30% of the 50% of production costs [3]. This shows that the ground layout is essential in the production, directly affecting business results in terms of cost, process completion time, and productivity [4]. The facilities layout problem is a high complexity computational theory problem (nondeterministic polynomial-hard (NP-hard)).[5], the problem is not solved in a short time, and the complexity can grow exponentially with the number of n that needs to be solved. For instance, to lay out 20 facilities, the number of options is 20! = 2,432902e+18 [6]. The basic problem is built into the quadratic assignment problem (QAP) [7], which has two unsolved problems in resource allocation. These problem are predefined locations on the ground, the equation to solve these problem was proposed by Koopmans and Beckmann in 1957, in addition to other methods, such as dynamic programming [8], Branch and Bound [9], and linear integer programming [10].

This paper presents research on application of (M-ALOB) algorithm to find the optimal solution for the problem of website layout. The article is presented as follows. Section 1 introduces the problem of floor layout. Section 2. Literature review, assessment of relevant research documents. Section 3 Research methods of algorithms and techniques applied to construction problems. Section 3 presents the numerical results generated from the (M-ALOB) algorithm. Conclusions and discussions are given in Section 4.

2. Literature review

Scientists have used meta-heuristic algorithms to solve discrete problems in QAP, these methods find the optimal solution by searching and exploring. Some old and improved algorithms are widely used such as genetic algorithm GA [11], swarm optimization PSO [12], artificial bee colony ABC [13]. Previous studies often used GA to solve discrete problems in QAP, but previous studies often limited repetition of old algorithms; The new improved algorithm has not completely overcome the limitations of the old algorithm, the input data is cumbersome and the results are not comparable with other algorithms, see Table 1. Previous studies on the rac problem discrete QAP.

In recent years, meta-heuristic algorithms have been strongly applied in many fields, especially optimization problems, and have achieved remarkable results such as Dildar Gürses [14]. comparing real-world engineering application arithmetic optimization algorithms, Betül Sultan Yıldız [15] comparing political optimization algorithms to design optimization in industry, Betül Sultan Yıldız [16] Conceptual comparison of eco-geography-based algorithms for optimal product design, Shubham Gupta et al [17] compare metaheuristic optimization algorithms to solve mechanical design optimization problems limit. In construction, the meta-heuristic algorithm has also solved many optimization problems in terms of time, cost, and progress, with impressive results such as Pham Vu Hong Son, Tran Trong Khoi [18] developing the algorithm. African wild dog math to optimize freight coordination, Pham Vu Hong Son, et al [19] Optimizing construction material costs using hybrid dragonfly algorithm—particle swarm optimization, Hong Son, et al al [20] Utilizing artificial intelligence to solving time–cost–quality trade-off problem, Hong Son, et al [21] Optimization in Construction Management Using Adaptive Opposition Slime Mold Algorithm.

Table 1
Previous studies using problem solving algorithms (CSLP) [22–26].

Year	Author	Research	Limitations of the study
2000	H. Li P. E. D. Love	A genetic algorithm based on Darwin's theory of evolution is used to solve the facility layout problem on a construction site, presented as the allocation of facilities to a set of locations. pre-determined and concurrently satisfy the constraints.	GA algorithm is less capable of local search, the study did not examine the effect of parameters such as cross-swapping probability and mutation probability on convergence.
2002	S.-O. Cheung T. K.-L. Tong C.-M. Tam	The GA genetic algorithm model was developed to find an almost optimal solution in arranging the facilities of the precast concrete factory on the construction site with different transportation costs.	The study was effective in testing with a small population size and a relatively short convergence process.
2009	K. Lam X. Ning M. Lam	Max-min MMAS ant colony system initializes the initial population better than the randomly generated initial population of GA, the MMAS-GA algorithm is formed by connecting MMAS in the initialization step of GA. proposed to solve the problem of arrangement of facilities on the construction site.	The proposed MMAS-GA algorithm is applied only for one case study, the effectiveness of the algorithm needs to be tested with other studies in the field of construction management.
2010	C. Huang C. K. Wong C. M. Tam	It is proposed to optimize the operation of using hoists for material transport and material storage locations in high-rise buildings by the mixed integer program MIP.	Research should extend the formulation of problems by adding additional linear constraints to consider more complex situations.
2008	S. Önüt U. R. Tuzkaya B. Doğaç	The swarm optimization algorithm PSO was developed for an optimal layout that minimizes the annual transportation costs in a distributed warehouse, different products are received from different suppliers, stored in stock for a specified period of time and distributed to different customers.	The modified PSO algorithm has some shortcomings regarding the time to find solutions when the problem to be solved is the variable using continuous decimal data.

This study proposes to improve the M-ALOB algorithm by crossing the ALO lion ant introduced in 2015 by the mathematician Mirjalili [27] with the MC mutation and hybridization strategy [28]. on the [13] position from the original ALO to overcome these limitations and speed up the convergence to produce the optimal result in the shortest time. So far, ALO has solved many problems in fields such as power supplies, computer science, medical applications, wireless networks, control engineering and others, but it is completely new in the field of computing. solution (CLSP) is simulated as QAP. More than 10 journals have published ALO articles, many of which have upgraded ALO [29], such as Emary et al. [29] proposed three binary variants of ALO using two approaches (BALO) [30], Kumar et al. [31] improved the roulette wheel by replacing the ALO ant update equation, and Subhashini and Satapathy [32] introduced an enhanced version of ALO (e-ALO) that applied a random function to generate random numbers in the range [0,1] instead of a uniformly distributed function.

3. Research methodology

3.1. Ant Lion Optimizer (ALO)

3.1.1. Algorithm inspiration

Ant Lion Optimizer ALO was proposed by mathematician Seyedali Mirjalili. ALO mimics Ant Lion's intelligent behavior in hunting ants in the wild. Five main steps in hunting include: *(i) Random walks of ants, (ii) Trapping in antlion's pits, (iii) Building trap, (iv) Sliding ants towards antlion, (v) Catching prey and re-building the pit. see* Figure 4.

Antlions have a unique hunting behavior with their favorite prey. Antlion will dig a conical pit in the sand by walking in a circle and throwing sand out with its giant jaws. Figure 1 shows several conical pits of different sizes and shapes. After digging the trap Antlion hides at the bottom of the cone (like a waiting predator) and waits for insects (preferably ants) to be trapped in the pit. Figure 2.

Fig. 1. Ant Lion's cone-shaped trap [33].

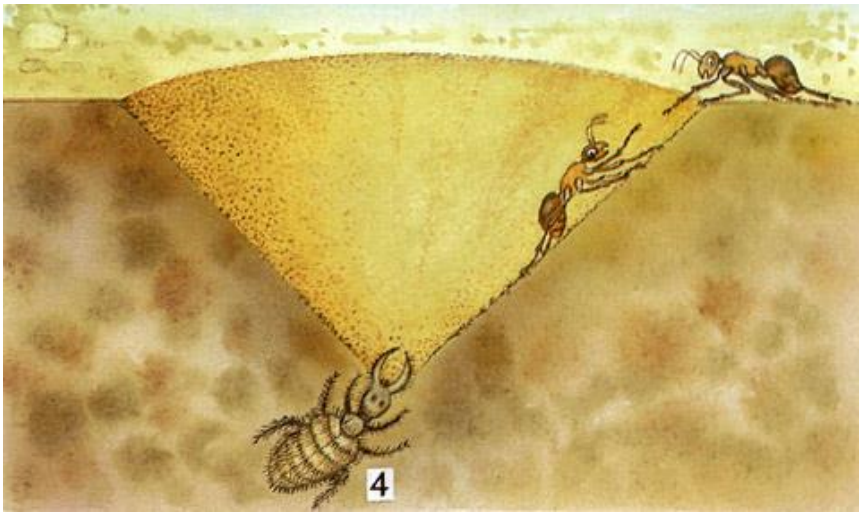


Fig. 2. Antlion waits for an ant in the trap [34].

3.1.2. Mathematical model

Antlion hunting starts with random walks in the search space, shown by the following equation:

$$X(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \dots, cumsum(2r(t_n) - 1)] \quad (1)$$

n is the maximum number of iterations, t is step of random walk (iteration in this study), cumsum calculates the cumulative sum and r(t) is a stochastic function defined as follows:

$$r(t) = \begin{cases} 1 & if \quad rand > 0.5 \\ 0 & if \quad rand \leq 0.5 \end{cases} \quad (2)$$

Where t is the step of random walk (iteration in this study) and *rand* is a random number generated with uniform distribution in the interval of [0,1]. Figure 3 shows an illustration of five random walks per 1000 iterations. This figure shows that the random walk fluctuates significantly around the base position, trending up or trending down.

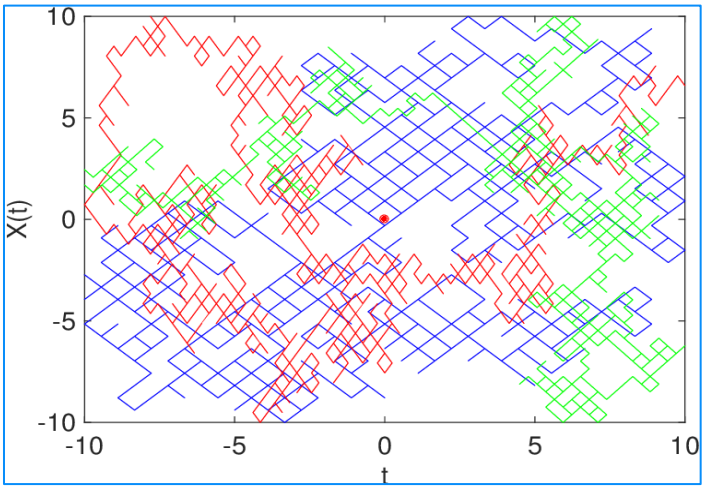


Fig. 3. Random crawls of ants [35].

The ALO is based on the number of ants and during optimization in the following matrix:

$$M_{Ant} = \begin{bmatrix} A_{1,1} & A_{1,2} & \dots & \dots & A_{1,d} \\ A_{2,1} & A_{2,2} & \dots & \dots & A_{2,d} \\ : & : & : & : & : \\ : & : & : & : & : \\ A_{n,1} & A_{n,2} & \dots & \dots & A_{n,d} \end{bmatrix} \tag{3}$$

$$M_{Antlion} = \begin{bmatrix} AL_{1,1} & AL_{1,2} & \dots & \dots & AL_{1,d} \\ AL_{2,1} & AL_{2,2} & \dots & \dots & AL_{2,d} \\ : & : & : & : & : \\ : & : & : & : & : \\ AL_{n,1} & AL_{n,2} & \dots & \dots & AL_{n,d} \end{bmatrix} \tag{4}$$

where n is the number of ants. M_{Ant} is a matrix that saves the positions of ants, $A_{i,\ j}$ shows the value of the *j*-th dimension of the *i*-th ant. *d* is the number of variables.

n is the number of Antlions, $M_{Antlion}$ is the matrix that saves the positions of Antlions, $AL_{i,\ j}$ represents the *j*-th dimensional value of the *i*-th Antlion, *n* is the number of Antlions, *d* is the number of variables.

To evaluate the strength of each ant and Antlion, an objective function is used and stored in the following matrix:

$$M_{OA} = \begin{bmatrix} f\left(\left[A_{1,1}\ A_{1,2}\ \dots\ \dots\ A_{1,d}\right]\right) \\ f\left(\left[A_{2,1}\ A_{2,2}\ \dots\ \dots\ A_{2,d}\right]\right) \\ : \\ : \\ f\left(\left[A_{n,1}\ A_{n,2}\ \dots\ \dots\ A_{n,d}\right]\right) \end{bmatrix} \tag{5}$$

$$M_{OAL} = \begin{bmatrix} f\left(\left[AL_{1,1}\ AL_{1,2}\ \dots\ \dots\ AL_{1,d}\right]\right) \\ f\left(\left[AL_{2,1}\ AL_{2,2}\ \dots\ \dots\ AL_{2,d}\right]\right) \\ : \\ : \\ f\left(\left[AL_{n,1}\ AL_{n,2}\ \dots\ \dots\ AL_{n,d}\right]\right) \end{bmatrix} \tag{6}$$

where M_{OA} is the matrix for saving the fitness of each ant, $A_{i,\ j}$ shows the value of the *j*-th dimension of the *i*-th ant, *n* is the number of ants.

M_{OAL} is the matrix for saving the fitness of each AntLion, $AL_{i,\ j}$ shows the value of the *j*-th dimension of the *i*-th Antlion, *n* is the number of Antlions, *d* is the number of variables and *f* is the objective function.

Normalized using Ants update their positions with random walk at every step of optimization every search space using the following equation:

$$X_i^t = \frac{(x_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \tag{7}$$

where i is the variable, t is the iteration, a_i is the minimum of random walk, b_i is the maximum of random walk, c^t_i is the minimum of variable at iteration and d^t_i indicates the maximum of variable at iteration.

When ants fall into Antlion's trap, they instinctively want to get out of there. Antlion begins to throw sand at the ants hindering their escape and sends them towards the bottom of the pit. It is shown by equations (8), (9), (10), (11), (12).

$$c_i^t = Antlion_i^t + c^t \tag{8}$$

$$d_i^t = Antlion_i^t + d^t \tag{9}$$

$$c^t = \frac{c^t}{I} \tag{10}$$

$$d^t = \frac{d^t}{I} \tag{11}$$

$$I^t = 10^w \frac{t}{T} \tag{12}$$

where c^t is the minimum of all variables at t-th iteration, d^t is the vector including the maximum of all variables at t-th iteration, c^t_i is the minimum of all variables for i-th ant $d^t{}_i$ is the maximum of all variables for i-th ant, $Antlion^t_j$ indicates the j-th position of Antlion at the t-th iteration, and I is the slip rate change as shown in the following equation.

$$\mathrm{I} = \begin{cases} 1 + 10^6 \frac{t}{Tmax} & \text{if } 0.95\mathrm{Tmax} < \mathrm{t} < \mathrm{Tmax} \\ 1 + 10^5 \frac{t}{Tmax} & \text{if } 0.9\mathrm{Tmax} < \mathrm{t} < 0.95\mathrm{Tmax} \\ 1 + 10^4 \frac{t}{Tmax} & \text{if } 0.75\mathrm{Tmax} < \mathrm{t} < 0.9\mathrm{Tmax} \\ 1 + 10^3 \frac{t}{Tmax} & \text{if } 0.5\mathrm{Tmax} < \mathrm{t} < 0.75\mathrm{Tmax} \\ 1 + 10^2 \frac{t}{Tmax} & \text{if } 0.1\mathrm{Tmax} < \mathrm{t} < 0.5\mathrm{Tmax} \\ 1 & \text{otherwise} \end{cases} \tag{13}$$

where $T\,m\,a\,x$ is maximum iteration. Ants walk and are positioned around the elitist Antlion and Antlion is selected according to the roulette wheel with the following mathematical model.

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{14}$$

where R^t_A is the Antlion selected by the roulette wheel on the t-th iteration and R^t_E is the elitist Antlion obtained by equation (7) for each t-th iteration. After hunting, the Antlions update their position with the position of the ants according to the fitness value using the following equation:

$$Antlion_i^t = Ant_i^t \text{ if } f(Ant_i^t) < f(Antlion_i^t) \tag{15}$$

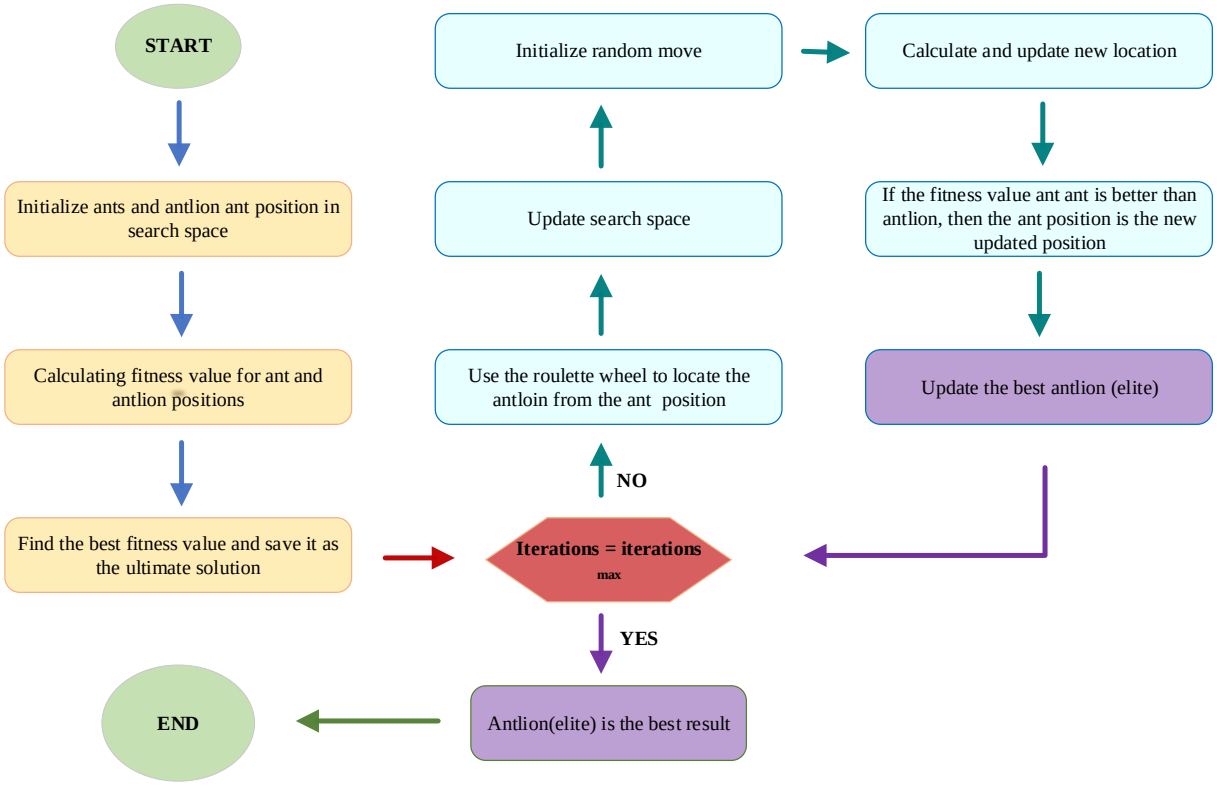

START
Initialize ants and antlion ant position in search space
Calculating fitness value for ant and antlion positions
Find the best fitness value and save it as the ultimate solution
END
Antlion(elite) is the best result
YES
Iterations = iterations max
NO
Use the roulette wheel to locate the antloin from the ant position
Update search space
Initialize random move
Calculate and update new location
If the fitness value ant ant is better than antlion, then the ant position is the new updated position
Update the best antlion (elite)

Fig. 4. Flowchart of ant lion optimizer [33].

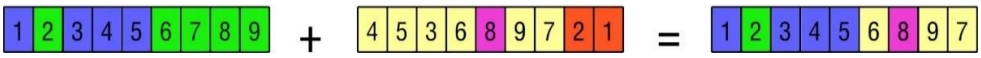
3.2. Mutation and crossover (MC) [36]

This method creates several variations of the migration algorithm during the stages of the Optimizer.

3.2.1 Crossover

The genetic algorithm combines two chromosomes (Parent A, Parent B) to produce a new chromosome (offspring) with a better probability that the crossover **Px** produces a new offspring.

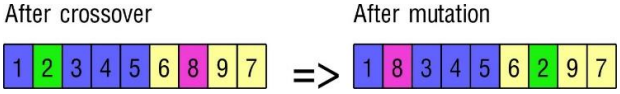
Parent A Parent B offspring



(16)

3.2.2 Mutation

After crossover, the offspring is mutated, the mutation helps prevent the algorithm from local Optimizer, exploring the entire search space, maintaining diversity in the population. Modifying the genes of a selected chromosome with a probability of mutation **Pm**. Reversing the bits of the selected chromosome.



(17)

3.3. Opposition-based learning (OBL) [37]

Opposition-based learning OBL introduced by Tizoosh et al. [13] ensures an acceleration in the convergence process by comparing the opposite number with the selected outcome and finding the better one to keep for the next population to accelerate convergence. The period of convergence depends on the distance of the original result point to the Optimizer result point.

3.3.1. Definition 1

Opposition-based learning OBL was conceptualized by Rahnamayan et al. [38] that search space is transformed into opposite search space, one-dimensional search space can be extended in many dimensions. "If y is a search point in space, where $p \in [LB, UB]$, a new solution is p^* in transformed space which is expressed by the following equation:

$$p^* = LB + UB - p \tag{18}$$

3.3.2. Definition 2

Opposition-based learning OBL for high dimension, Rahnamayan et al. [38] conceptualized that, if $P \in (p_1, p_2 \ldots, p_D)$ then D is a point in the search space, $p_1, p_2 \ldots, p_D \in R$, where R is space Euclidean và $p_i \in [LB_i, UB_i]$, $\forall_i \in (1, 2, \ldots, D)$, then the new transformed feasible solution is determined by the equation:

$$p_i^* = LB_i + UB_i - p_i \tag{19}$$

The original population and the opposite population are evaluated and the best fitness value is selected through the equation

$$f(p) \leq f(p^*) \tag{20}$$

where $f(p)$ defines the fitness value at the original point and $f(p^*)$ defines the fitness value of the opposite point, if $f(p) \leq f(p^*)$, y will be replaced by p^*, otherwise continue searching. see Figure 5

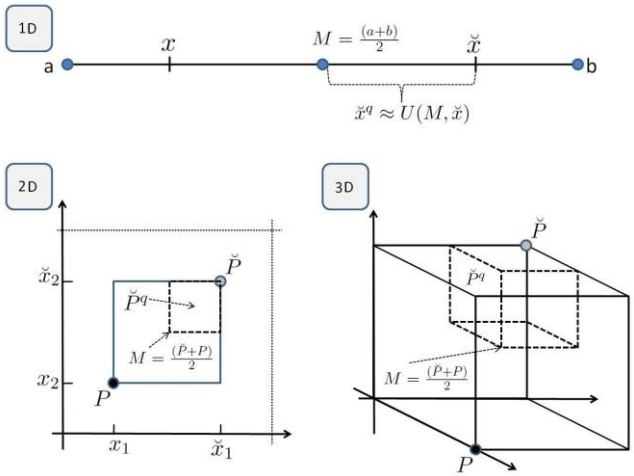


Fig. 5. Illustration of a point and its corresponding opposite in one-, two-, and three-dimensional spaces [38].

After combining the original ant-lion algorithm ALO with mutation and interference MC methods, Opponent Based Learning OBL. We have a diagram of the new algorithm M-ALOB, see Figure 6.

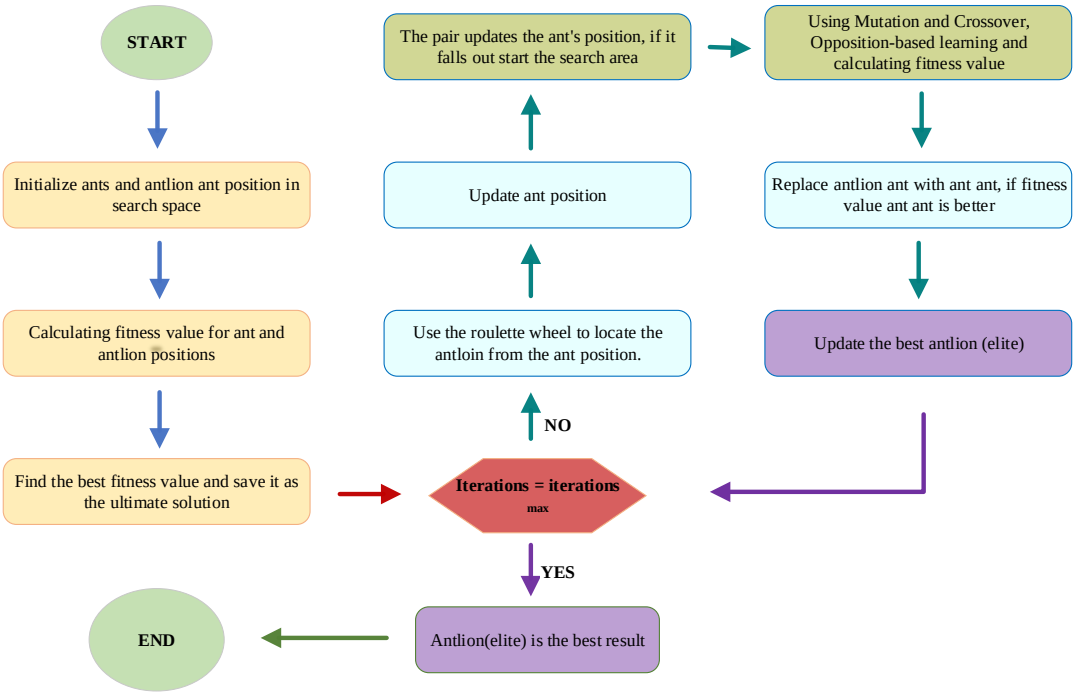

START
Initialize ants and antlion ant position in search space
Calculating fitness value for ant and antlion positions
Find the best fitness value and save it as the ultimate solution
Iterations = iterations max
NO
YES
Use the roulette wheel to locate the antloin from the ant position.
Update ant position
The pair updates the ant's position, if it falls out start the search area
Using Mutation and Crossover, Opposition-based learning and calculating fitness value
Replace antlion ant with ant ant, if fitness value ant ant is better
Update the best antlion (elite)
Antlion(elite) is the best result
END

Fig. 6. Algorithm (M-ALOB) flowchart.

3.4. Construction site layout problems– CSLPs.

Problem (CSLPs) focus on the arrangement of facilities on a construction site such as machinery, equipment or operating rooms in a predefined shape. Layout issues refer to (i) determining the size and shape of the base; (ii) determine the constraints between the facilities; and (iii) determine the relative location of facilities that allow for efficient operation. The goal is for facilities to operate efficiently on site.

Efficient facility layout improves building performance. Furthermore, facility layout is often a costly long-term investment, disrupting the flow of materials and worker activity. Therefore, rational layout planning reduces construction costs (plant, labor and materials), increases labor and equipment productivity (labor time and equipment time) and improves safety (hazardous materials, falling objects and waste) on construction sites.

(CSLPs) can be constructed as QAP. The objective function of this study is to minimize the flow of work transport between facilities on the site, which depends mainly on two factors: the density of work flow (Cij) between facilities facilities and the distance (dkl) between their locations [39].The objective functions of (CSLPs) are defined as follows:

$$min\, z = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{m=1}^{n} A_{ijkm}X_{ij}X_{km} \tag{21}$$

$$\sum_{i=1}^{n} X_{ij} = 1, j = 1, \ldots\ldots, n$$

$X_{ij} \in \{0,1\}, i,j = 1,\ldots..,n$

where:

$x_{ij:}$ 1 if department i is assigned to location j, 0 otherwise

$x_{km:}$ 1 if facilities k is ascription to location m, 0 otherwise

c_{ij}: cost per unit time associated directly with assigning department i to location j

$d_{jm:}$ 'distance' from location j to location 1 (travel cost between locations)

f_{ik}: work flow from department i to department k.

$A_{ijkm} = f_{ik}, d_{jm}$ if i ≠k or j ≠m.

$A_{ijkm} = c_{ij}$ if i = k or j = m.

4. Calculation case

4.1. Case study 1

This problem is used from the study of Lam et al. The total construction site includes the foundation, structure, installation of services in the work, there are 9 essential means to be considered to simplify the complexity of the CSLP problem in this problem [24],

1. Garbage area
2. Soap area
3. Rebar bending area
4. Wood workshop area
5. Worker Zone
6. Material storage area
7. Main Gate
8. Hoist
9. Security house, office

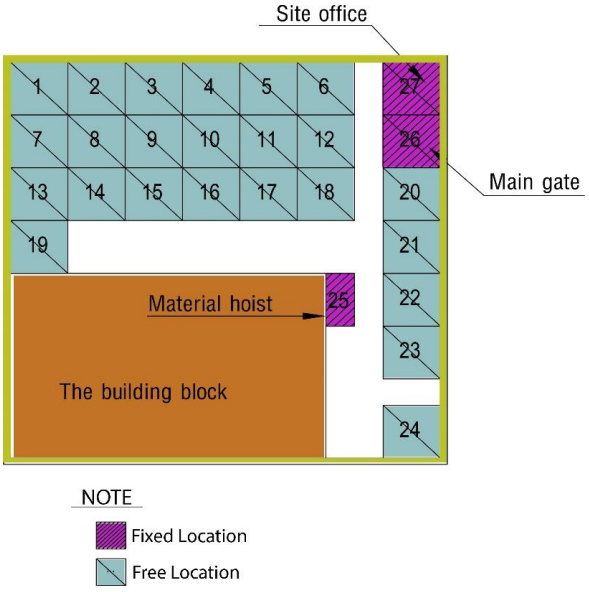


Fig. 7. Simple assumed construction site layout.

In which there are three fixed bases are the main gate, the hoist and the office area. The main gate location is predefined in relation to construction traffic. Security houses, offices are placed in front of the entrance to ensure labor safety and security for accreditation. See figure 7, the

positions on the construction site are simply defined as a 2m x 2m square. Index of proximity frequency of establishments see Table 2.

Table 2
Workflows between site facilities.

	Proximity index of inter-facility workflow								
Facility /No.	1	2	3	4	5	6	7	8	9
1	0	3.1	0.8	0.6	0.6	0.9	1.7	0.4	0.4
2	3.1	0	2.1	1.9	1.5	1.5	3.2	1.2	1.2
3	0.8	2.1	0	1.6	1.9	1.2	3.6	5.2	1.9
4	0.6	1.9	1.6	0	1.8	2.1	3.1	5.1	1.9
5	0.6	1.5	1.9	1.8	0	2.2	2.3	1.5	2.3
6	0.9	3.2	1.2	2.1	2.2	0	3.6	4.5	2.5
7	1.7	3.2	3.6	3.1	2.3	3.6	0	2.5	2
8	0.4	1.2	5.2	5.1	1.5	4.5	2.5	0	1.5
9	0.4	1.2	1.9	1.9	2.3	2.5	2	1.5	0

Run the problem 30 times on PyCharm 2022a software to evaluate the accuracy of the optimal results from the algorithm M-ALOB see table 3 for the optimal results of 30 runs of the problem, and table 4 for the results after 30 runs to evaluate the accuracy of the results.

Table 3
Results of optimal running 30 times from M-ALOB algorithm.

No.	Solution		Value
1	23 22 21 20 18 17	26 27 25	755.31
2	06 12 21 22 20 18	26 27 25	688.40
3	11 12 18 21 06 20	26 27 25	689.21
4	11 12 18 21 06 20	26 27 25	689.21
5	23 22 21 20 18 17	26 27 25	755.31
6	23 22 21 20 18 17	26 27 25	755.31
7	06 12 22 21 20 18	26 27 25	689.41
8	11 12 18 21 06 20	26 27 25	689.21
9	17 18 22 21 12 20	26 27 25	689.12
10	06 12 21 22 20 18	26 27 25	688.40
11	12 20 18 23 22 21	26 27 25	725.93
12	12 18 22 22 21 20	26 27 25	712.31
13	06 12 21 22 20 18	26 27 25	688.40
14	16 18 22 21 12 18	26 27 25	689.12
15	05 12 21 22 20 18	26 27 25	688.40
16	11 12 18 21 06 20	26 27 25	689.21
17	23 22 21 20 18 17	26 27 25	755.31
18	06 12 22 21 20 18	26 27 25	689.41
19	23 22 21 20 18 17	26 27 25	755.31
20	11 12 18 21 06 20	26 27 25	689.21
21	12 17 22 21 20 18	26 27 25	703.82
22	06 12 20 22 21 18	26 27 25	688.40
23	11 12 18 21 06 20	26 27 25	689.21
24	17 18 22 21 12 20	26 27 25	689.12
25	11 12 18 21 06 20	26 27 25	689.21
26	06 12 22 21 20 18	26 27 25	689.41
27	11 17 18 21 12 20	26 27 25	691.22
28	23 22 21 20 18 17	26 27 25	755.31
29	06 12 21 22 20 18	26 27 25	688.40
30	12 18 23 22 21 20	26 27 25	712.31

Table 4
Descriptive statistics after 30 runs.

	N	Minimum	Maximum	Mean	Std. Deviation
Total cost	30	688.40	755.31	705.33	26.778
Valid N (listwise)	30				

The results obtained after 30 independent runs show that the values range from $688.40 to $755.31, the standard deviation of $26,778 is quite small compared to the mean of 705.33, which means it fluctuates around. average value is very low. From here it is shown that the M-ALOB algorithm has stable results

Table 5
Optimal results found GA, ALO, M-ALOB.

Facility		1	2	3	4	5	6	7	8	9	Optimum value
Location	GA	9	11	20	22	16	17	26	27	25	857.99
	ALO	06	12	18	21	11	20	26	27	25	694.07
	M-ALOB	06	12	21	22	20	18	26	27	25	688.40

Table 5 shows the results obtained by the algorithm M-ALOB with two traditional algorithms GA and the algorithm ALO, through 30 runs of the results, we see the results M-ALOB gives the most optimal value, the earliest convergence. The optimal value of the algorithm M-ALOB min=688.4 lower GA is 19.7%, lower ALO is 0.8%.

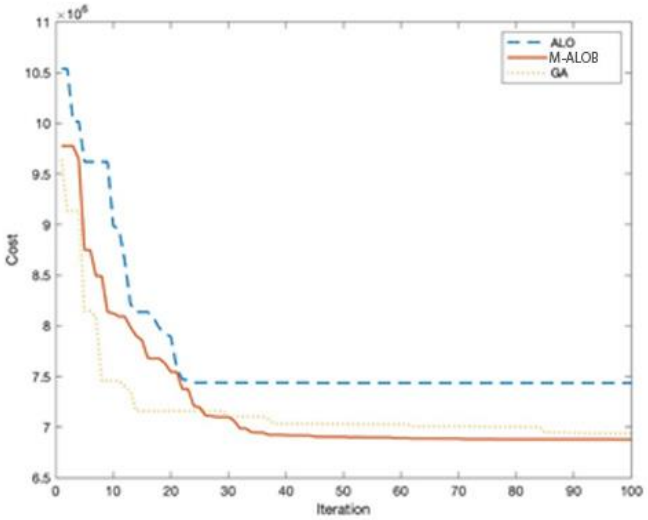


Fig. 8. Comparison of results and convergence speed between algorithms GA, ALO, M-ALOB.

Figure 8 shows that the convergence curve obtained from the algorithm M-ALOB for each run has the most stable results for QAP problem solving. Algorithm M-ALOB confirms high convergence acceleration, increasing number of iterations and efficient optimal global space search.

To demonstrate that M-ALOB contributes and improves, this study also compares the results of the algorithm's layout of facilities on the premises M-ALOB with the results of previous studies GA . A higher rating scale indicates that the facility should be placed as close to each other as

possible and a lower rating scale indicates that the facility should be further away from other facilities . The result of the construction site layout can be seen in Figure 9, Figure 10.

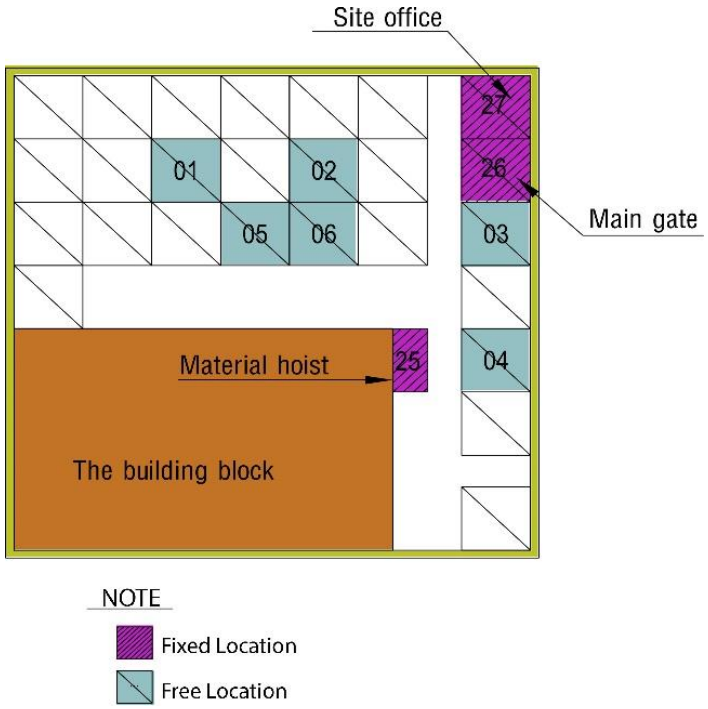


Fig. 9. Optimizing location on construction site – GA.

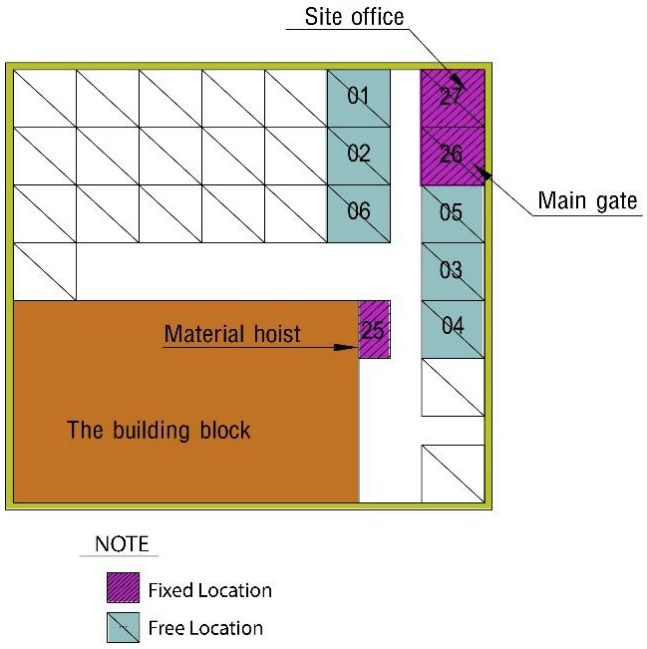


Fig. 10. Optimizing the location on the construction site using the M-ALOB.

The results of Figure 9, Figure 10 show that the algorithm M-ALOB arranges facilities closer together than the results from the algorithm GA, M-ALOB has a higher rating scale. compared to GA. It shows that M-ALOB is suitable for problem processing QAP.

4.2. Case study 2

The total construction site in the construction phase of the rough part together with the equipment and machinery transporting materials is gathered to the construction site in a large volume, so it is necessary to arrange a reasonable and convenient place to gather materials on the site for construction organization. Total construction site see Figure 11. There are 15 essential means to be considered to simplify the complexity of the problem (CSLPs) in this problem.

01. Site protection 1
02. Site protection 2
03. Car wash bridge
04. Briefing + guests
05. Rest room for technical staff
06. Technical staff working room
07. Only cancel the site leader
08. Construction site toilets
09. Closed material warehouse
10. Tool Warehouse
11. Steel cutting and bending area
12. Sand and rock beach
13. Site health
14. Canteen
15. Room for workers.

In which there are three fixed bases: guard house 1, guard house 2, car wash bridge. These three bases are predefined in relation to the master plan of the work site. Guard house 1 and guard house 2 are placed in front of the entrance to ensure safety and security for workers. The bridge is fixed at the entrance gate to clean the motor vehicle before running out of the construction site.

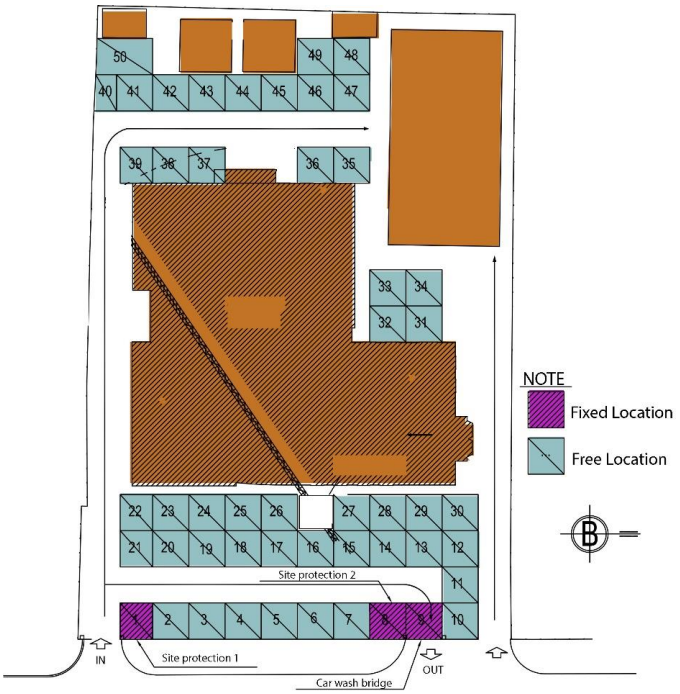


Fig. 11. Simple assumed construction site layout.

In Figure 11 the locations on the construction site are simply defined as a square of 5m x 5m. The proximity index of facilities is shown in Table 6. Run the problem 30 times on PyCharm 2022a software to evaluate the accuracy of the optimal results from the algorithm M-ALOB See table 7 for the optimal results of 30 runs of the problem, and table 8 for the results after 30 runs to evaluate the accuracy of the results.

Table 6
Workflows between site facilities.

Facility /No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0														
2	86.2	0													
3	82.2	84	0												
4	82.3	84.3	84.1	0											
5	82.3	83.6	83.8	84.5	0										
6	82.4	85.5	83.9	84.7	84.7	0									
7	0.6	0.6	0.2	0.2	0.2	0.8	0								
8	82.7	83.1	87.2	87.2	84.1	86.7	85.2	0							
9	82.5	83.2	83.9	83.8	84.3	84.8	85.5	80.4	0						
10	83.1	82.1	81.6	81.8	82.2	83.6	82.5	82.7	83.9	0					
11	80.8	81.9	81.9	82.1	82.3	84.5	87.9	85	85.2	80.8	0				
12	80.6	81.5	81.2	83.1	81.5	3.1	88.9	81.2	86	82.2	80.6	0			
13	80.6	83.2	83.6	85.1	82.3	87.1	85.5	83.1	89.2	83.6	82.3	80.9	0		
14	0.6	0.9	0.8	0.6	0.4	0.2	0.7	0.6	0.7	0.4	0.6	0.2	0.7	0	
15	0.1	0.2	0.6	0.4	0.6	0.6	0.6	0.7	0.2	0.2	0.8	0.7	0.4	0.8	0

Table 7
30-fold Optimal Results M-ALOB.

No.	Solution	Value
1	01 08 09 05 16 06 24 17 26 04 25 19 18 15 27	178,329.43
2	01 08 09 06 05 04 27 18 07 26 17 15 16 19 03	175,395.77
3	01 08 09 06 05 07 25 15 17 04 26 18 16 14 27	174,017.47
4	01 08 09 15 06 07 25 05 17 04 18 26 16 27 28	174,089.26
5	01 08 09 05 06 07 25 16 17 04 26 18 15 14 27	174113.55
6	01 08 09 06 07 17 29 16 14 28 27 13 15 05 04	172,049.03
7	01 08 09 06 05 07 25 04 17 16 18 26 15 19 03	174,220.17
8	01 08 09 05 06 07 25 03 16 18 17 26 15 14 27	174,155.71
9	01 08 09 06 07 03 26 05 16 03 08 15 17 19 25	176,368.82
10	01 08 09 05 07 06 25 04 16 17 18 26 15 19 02	174,504.63
11	01 08 09 06 05 07 25 16 18 04 26 19 17 15 27	176,609.25
12	01 08 09 07 27 28 26 16 15 14 13 17 06 05 29	176,507.34
13	01 08 09 06 05 07 25 04 17 16 26 18 15 14 27	174,236.41
14	01 08 09 13 07 06 26 14 27 17 16 28 15 29 12	173,986.97
15	01 08 09 07 14 28 26 15 16 17 27 05 06 13 29	173,774.92
16	01 08 09 15 17 27 30 14 13 12 29 11 18 16 10	174,292.98
17	01 08 09 15 27 16 30 28 12 14 29 11 13 10 25	174,215.79
18	01 08 09 06 07 17 29 16 14 27 28 13 15 11 30	**171,971.19**
19	01 08 09 05 06 07 25 15 17 04 16 18 26 14 27	174,154.41
20	01 08 09 06 05 07 28 16 15 17 27 26 14 29 13	173,402.56
21	01 08 09 28 13 29 17 14 15 07 16 05 27 04 26	174,126.11
22	01 08 09 16 07 15 19 17 06 26 18 04 05 03 27	176,131.62
23	01 08 09 06 07 14 26 25 27 05 16 18 17 13 28	173,934.03
24	01 08 09 05 06 07 25 04 16 17 18 26 15 19 02	174,185.99
25	01 08 09 14 07 05 26 06 16 28 17 27 15 04 18	174,175.10
26	01 08 09 04 06 07 26 16 27 17 15 18 05 14 25	175,568.85
27	01 08 09 07 06 17 29 14 27 16 28 13 15 11 12	171,973.55
28	01 08 09 15 07 14 18 16 05 26 17 03 04 27 25	175,142.92
29	01 08 09 16 07 06 12 15 14 27 13 29 27 10 11	173,715.08
30	01 08 09 17 07 06 29 15 14 13 26 28 16 11 12	172,422.13

Table 8
Cost statistics after 30 runs.

	N	Minimum	Maximum	Mean	Std. Deviation
Total cost	30	171,971.19	178,329.43	1,74E5	1,423.18
Valid N (listwise)	30				

The results obtained after 30 independent runs show that the values range from 171,971.19 to 178.329.43 USD, the standard deviation of 1,423.18 USD is quite small compared to the mean value $1.74x10^5$, which means the degree of variation. around the very low mean. From here it is shown that the algorithm M-ALOB has stable results.

Table 9
Optimal results found GA, ALO, M-ALOB.

	Facility	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Value
Location	GA	01	08	09	16	26	17	13	27	15	06	14	28	07	05	18	175,678.46
	ALO	01	08	09	29	12	13	02	26	03	11	28	05	16	10	21	238,059.41
	M-ALOB	01	08	09	06	07	17	29	16	14	27	28	13	15	11	30	**171,970.19**

After 30 runs, the results show that M-ALOB gives the most optimal value compared to GA and ALO. The optimal value of the algorithm M-ALOB min=171,970.19 lower GA is 2% and lower ALO is 27% see table 9.

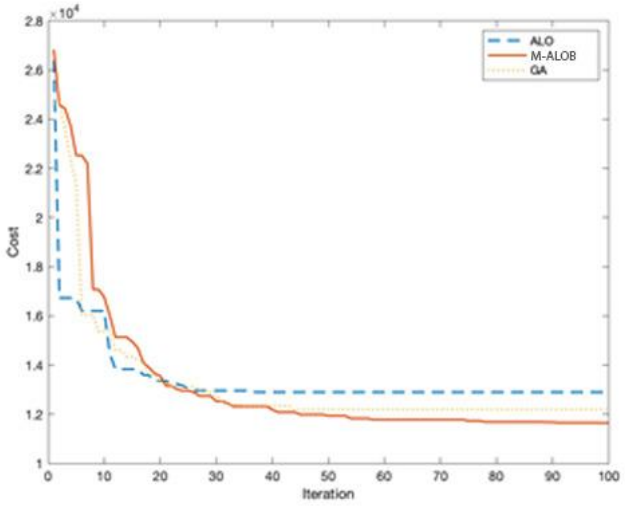


Fig. 12. Comparison of results and convergence speed between algorithms GA, ALO, M-ALOB.

Figure 12 shows the convergence curve obtained from the algorithm M-ALOB for each run with more stable results GA, ALO. The algorithm M-ALOB confirms high convergence acceleration, increasing number of iterations, and efficient optimal global space search.

Compare the results of the arrangement of facilities on the ground of the algorithm M-ALOB with the results of the study ALO. A higher rating scale indicates that the facility should be placed as close to each other as possible and a lower rating scale indicates that the facility should

be further away from other facilities . The result of the construction site layout can be seen in Figure 13, Figure 14

Fig. 13. Optimum location on building – ALO.

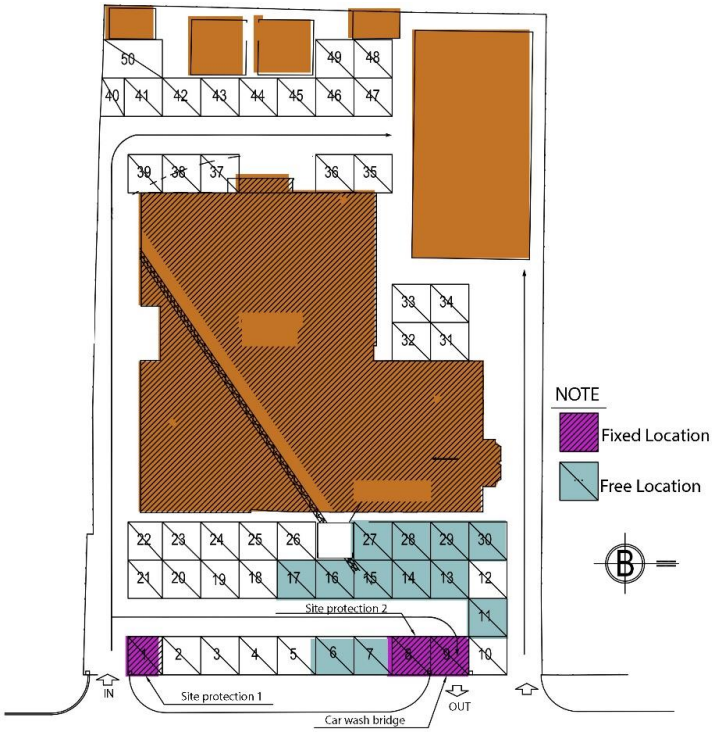


Fig. 14. Optimizing location on construction site - M-ALOB.

5. Discussion

In this paper, a new hybrid algorithm M-ALOB is proposed from the original algorithm ALO. M-ALOB has stable running results, has been tested for stability after 30 optimal runs in case study 1, case study 2 see table 5, table 9. Optimal results in case study 1 M -ALOB min=688.4 lower GA is 19.7%, lower ALO is 0.8% and case study 2 M-ALOB min=171,970.19 lower GA is 2% and less ALO is 27%. Arrangement of facilities on the premises through the algorithm M-ALOB gets the highest score, because the facilities are placed close together on the premises.

M-ALOB combined with mutation and crossover MC, and opposite-based learning OBL from the original algorithm ALO can be used to promote local optimization and increased discoverability and mining. MC creates some new transformations in the optimization and mutations that prevent local optimization. OBL accelerates the convergence process. However M-ALOB increases the computational complexity compared to the original algorithm ALO.

6. Conclusions

Develop a more general case study instead of focusing on transport, storage and facility layout by adding constraints: noise pollution reduction, unequal-sized facilities, fencing prevent movement in the construction site.

In this study, it is shown that parameter adjustment in the algorithm M-ALOB is very important. It is necessary to study deeply on the original theoretical problem to make the algorithm ALO run more stably.

Extend the applicability of M-ALOB to problems beyond the layout of the premises, for example, the application of M-ALOB to solve the logictics of transporting sand and rock by water from the storage station to the storage station location of the work to use, transport concrete by-products from the concrete supply station to the site where the work needs to be used. Application M-ALOB to the design of structural members such as the design of structural steel sections, welded connections or mechanical components such as propellers for ships.

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Data availability statement

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

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